In: 2025 International Conference on Control, Automation and Diagnosis (ICCAD), 1-3 July 2025, Barcelona, Spain
DOI:10.1109/iccad64771.2025.11099262

Multi-Agent Path Planning in Dynamic Environment with Communication Disruptions

1st Komsun Tamanakijprasart
Cranfield University, UK
k.tamanakijprasart.263@cranfield.ac.uk

2nd Sabyasachi Mondal
Cranfield University, UK
sabyasachi.mondal@cranfield.ac.uk

3rd Antonios Tsourdos
Cranfield University, UK
antonios.tsourdos@cranfield.ac.uk

***Abstract*—In this research, we present an innovative path-planning strategy specifically designed for a cooperative group of interconnected agents that are navigating in a synchronized formation through diverse environments, which include both stationary and moving obstacles that could hinder their progress. This strategy is developed by integrating Distributed Nonlinear Dynamic Inversion (DNDI) based leader-follower formation tracking control with the dynamic autorouting capabilities derived from the Interfered Fluid Dynamical System (IFDS). The proposed method exhibits a remarkable ability to effectively address the challenges posed by the absence of communication among agents, as well as the difficulties encountered when facing dynamic obstacles, all while ensuring that a safe distance is consistently maintained between all agents throughout their flight.**

***Index Terms*—multi-agent systems, UAV, dynamic path planning, formation flying**

I. Introduction

Multi-agent systems (MASs) have gained significant attention in computer science, finding applications in fields like robotics, distributed systems, economics, and autonomous vehicles. These systems consist of autonomous agents that interact with their environment and communicate with each other to achieve shared goals. One challenging application in MASs is path planning, where agents must navigate dynamic environments, avoid obstacles, and coordinate movements to prevent collisions. This becomes increasingly complex as the number of agents grows, especially in three-dimensional spaces like unmanned aerial vehicles (UAVs). In complex problems with numerous constraints and parameters, acting independently can lead to inefficient and unsafe outcomes. Simple cooperation mechanisms in MASs can help the group of agents increase their survival capacity and achieve their goals more effectively.

A. Contribution

In this research, we present a new strategy designed to enable collision-free flights for a group of UAVs under conditions of communication failure and the presence of unpredictable obstacles. The foundation of this approach is based on two main techniques: leader-follower formation flying, which uses Distributed Nonlinear Dynamic Inversion (DNDI) [1], and independent adaptive flying that utilises the Interfered Fluid Dynamical Systems (IFDS) [2], [3]. The proposed strategy outlines the logic for orchestrating these algorithms by providing methods of cooperation between agents. This strategy offers the following advantages:

1) *Lightweight and Real-Time Computation*: The solution forms of both the DNDI and IFDS algorithms are in closed forms, making them lightweight and supporting real-time computation. This is crucial in dynamic environments where rapid responses are required.
2) *Mathematical Proof*: Derived analytically, these algorithms have mathematical proofs that guarantee collision avoidance, providing a solid theoretical foundation and enhancing the system's reliability, particularly in safety-critical scenarios.
3) *Algorithm Transparency and Flexibility*: This approach provides complete algorithm transparency, allowing any part of the program to be adjusted as necessary. This enables the system to be tailored to specific requirements or constraints.

B. Related studies

Path planning for MASs presents significant challenges, particularly in coordination, which demands efficient communication mechanisms, planning strategies, and control architectures to enable effective decision-making in dynamic environments [4], [5]. Techniques such as safety barrier certificates and adaptive nonlinear control have been developed to address these issues, but require further refinement to manage parametric uncertainties effectively [6]. Geometric optimisation models provide a promising alternative, generating optimal flight trajectories by balancing distance, time, and track adjustment costs [7]. The Interference Fluid Dynamical System (IFDS) [2], [3] appears to have high practicality in terms of low-cost computation, real-time execution, and dynamic obstacle avoidance in 3D environments. Although the success of the hybrid IFDS algorithm has been reported in many pieces of literature [8]–[14], the use of IFDS algorithms in MASs has not been much investigated. Recently, multi-agent reinforcement learning (MARL) has been introduced to improve decision-making in UAV swarms, offering improvements in tracking success rates and energy efficiency, yet it still struggles with real-time adaptability to unpredictable target movements [15] [16]. Deep Reinforcement Learning (DRL) is effectively used in dense, heterogeneous environments, with recent advancements like the Orientated Bounding Capsule (OBC) and a velocity-related

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The final published version (version of record) is available online at DOI:10.1109/iccad64771.2025.11099262. Please refer to any applicable publisher terms of use.

collision risk function improving success rates and safety in congested scenarios [17].

Autonomous formation flying significantly enhances the scalability and flexibility of autonomous flight systems of multiple vehicles. Decentralised self-organised control is another key principle in MASs where each agent operates based on local information, allowing for scalability and robustness in dynamic environments [18]. In models of behaviour dynamics and flocking behaviour in birds, each agent can adjust their direction based on the average direction of their neighbours, leading to consensus and cohesive movement [19], [20]. Rezaee et al. further contribute by introducing an $\mathcal{H}_\infty$ control strategy that ensures motion synchronisation in the presence of communication delays [21]. Padhi et al. present a nonlinear integrated guidance and control approach that quickly establishes and maintains formations in various scenarios [22]. The modified tentacle algorithm addresses challenges in formation flight in the high-speed and unstructured environment by rapidly matching steering commands to tentacle radii [23]. Ali and Montenegro's work on a centralised control scheme with adaptive LQR PI controllers allows for dynamic formation changes even with communication losses [24]. Xiaohua et al. propose a scalable adaptive formation control protocol, utilising radial basis function neural networks to model vehicle dynamics and repulsive potentials for obstacle avoidance. This protocol ensures collision-free formation tracking without requiring global information of the interaction topology [25]

II. Preliminaries

A. Leader-follower Consensus Tracking of Multiple Agents

Let us consider N nonlinear agents, called followers, connected by a communication topology. Agents need to follow the trajectory of a leader $X_L(t)$ connected to a few networked agents. If the followers' states, i.e., $X_i(t); i = 1, 2, \ldots, N$ achieve the consensus and track the leader's states, i.e., if $X_i(t) \to X_L(t)$ as $t \to \infty$, the followers are considered to achieve consensus trajectory tracking.

$$\forall i \in \{1, 2, ..., N\}, \lim_{t\to\infty} X_i(t) = X_L(t)$$

B. Graph Theory

The agents share their own information on a communication topology represented as a weighted undirected graph $G = \{V, E\}$. The graph consists of vertices and nodes. Each vertex of the set $V = \{v_1, v_2, \ldots, v_N\}$, represents an agent. Communication among agents is presented by a set of edges, $E \subseteq V \times V$ in the graph. The weighted adjacency matrix A describes the communication topology of the graph. Its elements a_{ij} are greater than zero if there exists an edge between the vertices v_i and v_j (i.e., $(v_i, v_j) \in E$), otherwise, a_{ij} equals zero. The matrix A has zero diagonal elements since there are no self-loops in the graph, i.e., $v_i \in V$ implies $a_{ii} = 0$. The degree matrix $D \in \mathbb{R}^{N\times N}$ is a diagonal matrix with elements $d_i = \sum_{j\in N_i} a_{ij}$, where N_i represents the neighbors of agent v_i. The Laplacian matrix, denoted by $L = D - A$, is used in this context. This study focuses on an undirected graph in which the weights have the property $a_{ij} = a_{ji}$. The graph is considered connected if there is a path between two nodes v_i and v_j in V. The array β_i shows if the i^{th} agent is connected to the leader.

III. Problem Formulation

We consider a multi-agent system featuring N follower UAVs in alliance with a leader UAV. The leader shares their own data, including position, velocity, heading, and various status updates, with the followers. The followers exchange information among themselves through the established communication topology to achieve and sustain the desired formation. However, there can be issues with the communication among agents, as shown in Fig. 1 and 2.

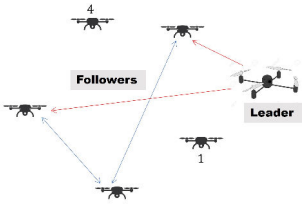

Figure 1: One or more followers lost communication with the leader.

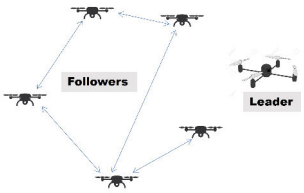

Figure 2: The leader lost communication with the followers.

A. Objectives

In this study, we aim to achieve the following goals:

- *Formation control*: We seek to arrange the agents into a geometric shape as specified by the leader (Vic formation with a separation distance of $d = 15\ m$ as depicted in Fig.3). The agents should maintain precise tracking of this formation throughout the operation.

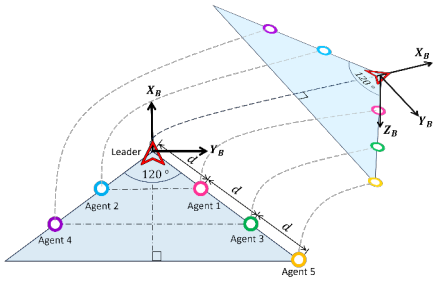

Figure 3: The Vic formation geometry forms a letter "V" where the leader aircraft is at the apex and its followers form an echelon to the left and right.

- *Autonomous obstacle avoidance*: The agents must possess the ability to autonomously navigate and reroute themselves in the presence of unforeseen static and dynamic obstacles.
- *Communication resilience*: We aim to develop a robust strategy that enables the agents to function effectively in the situation with reduced or absent communication, as depicted in Fig. 1 and Fig. 2.

B. Assumptions

- *Familiarity with the operational area*: We assume the information of static obstacles such as buildings and fixed structures is known. However, dynamic obstacles remain unpredictable, which will be detected using the onboard sensors equipped on the agents.
- *Modelling of obstacles*: Both static and dynamic obstacles are modelled using standard geometric shapes, including spheres, pipes, and cylinders. This simplification allows for behavioural analysis of the agents' interactions with their environment.

C. Agent and Leader dynamics

A point mass kinematics model is used to represent the UAV (agent) in this study. The i^{th} follower agent is described by

$$\dot{X}_i = f(X_i) + g(X_i)U_i, \qquad Y_i = X_i$$

where, $X_i \in \mathbb{R}^n$, $U_i \in \mathbb{R}^n$ are states and control respectively. f is a continuously differentiable vector-valued function representing the nonlinear dynamics.

Assumption 1: The matrix $g(X_i)$ is invertible for all time.

The leader dynamics are given by $\dot{X}_L(t) = f_L(X_L(t), t)$ where, $X_L \in \mathbb{R}^n$. f_L is piecewise continuous in t.

Assumption 2: $X_L(t)$ and $\dot{X}_L(t)$ are bounded.

IV. Methodology

A. Modeling of Environment

Objects such as trees, buildings, and aircraft can be simplified into cylinders, cones, spheres, or combinations. By doing this, the obstacle avoidance problem can be formulated for the IFDS method as solving for fluid streamlines avoiding the simplified shapes. The object-modelling function Γ can be expressed as follows:

$$\Gamma(\xi) = \left(\frac{x - x_0}{a}\right)^{2p} + \left(\frac{y - y_0}{b}\right)^{2q} + \left(\frac{z - z_0}{c}\right)^{2r} = 1$$

where $\xi = (x, y, z)$ is the aircraft's position, $\xi_0 = (x_0, y_0, z_0)$ is object's location, and (a, b, c) are the axes lengths of the object. Various shapes can be modeled using index parameters (p, q, r) as follows:

$$\begin{cases} \text{sphere}, & \text{if } p = q = r = 1. \\ \text{cylinder}, & \text{if } p = q = 1 \text{ and } r > 1. \\ \text{cone}, & \text{if } p = q = 1 \text{ and } r < 1. \\ \text{parallelepiped}, & \text{if } p > 1, q > 1 \text{ and } r > 1. \end{cases}$$

B. Leader-follower formation using Distributed Nonlinear Dynamic Inversion (DNDI)

The Distributed Nonlinear Dynamic Inversion (DNDI) [1] is a distributed control algorithm based on the robust Dynamic Inversion technique, designed to address the consensus issues in multi-agent systems. Benefiting from the robustness of nonlinear dynamic inversion (NDI), DNDI provides a closed-form solution for real-time applications and has been effectively used to resolve various consensus challenges [26], [27].

Algorithm 1 Leader-follower DNDI

1: Initialize $A, X_{i_0}, \beta_i, K_i, X_L$.
2: Calculate consensus tracking error of the i^{th} agent;

$$E_i = \left(\bar{d}_i + \bar{\beta}_i\right) X_i - \bar{a}_i \mathbf{X} - \bar{\beta}_i X_L$$

where $E_i \in \mathbb{R}^n$, $\bar{d}_i = (d_i \otimes \mathbf{I}_n) \in \mathbb{R}^{n \times n}$, $\bar{a}_i = (a_i \otimes \mathbf{I}_n) \in \mathbb{R}^{n \times nN}$, $\bar{\beta}_i = (\beta_i \otimes \mathbf{I}_n) \in \mathbb{R}^{n \times n}$, $X_L \in \mathbb{R}^n$, and $\mathbf{X} = [X_1^T \ X_2^T \ \dots \ X_N^T]^T \in \mathbb{R}^{nN}$.
3: Calculate consensus tracking error rate;

$$\begin{aligned} \dot{E}_i &= \left(\bar{d}_i + \bar{\beta}_i\right) \dot{X}_i - \bar{a}_i \dot{\mathbf{X}} - \bar{\beta}_i \dot{X}_L \\ &= \left(\bar{d}_i + \bar{\beta}_i\right) \left[f(X_i) + g(X_i)U_i\right] - \bar{a}_i \dot{\mathbf{X}} - \bar{\beta}_i \dot{X}_L \end{aligned}$$

4: Enforce the first-order error dynamics

$$\dot{E}_i + K_i E_i = 0$$

5: Substitute E_i and $\dot{E}_i$ in **step 4** to obtain the control. $U_i = (g(X_i))^{-1}\Big[-f(X_i) + \left(\bar{d}_i + \bar{\beta}_i\right)^{-1}\Big(\bar{a}_i \dot{\mathbf{X}} + \bar{\beta}_i \dot{X}_L - K_i\Big(\left(\bar{d}_i + \bar{\beta}_i\right) X_i - \bar{a}_i \mathbf{X} - \bar{\beta}_i X_L\Big)\Big)\Big]$

Remark. The consensus error contains the communication topology among followers (d_i) and between leader-followers (β_i). It indicates the coordinated teaming behaviours between multiple platforms.

C. Dynamic autorouting (DA) using Interfered Fluid Dynamical System (IFDS)

Both the follower and leader are equipped with the Dynamic Autorouting (DA) program [13], a real-time dynamic path planning solution for a UAV that enhances the IFDS algorithms with features such as safety functions, path-following strategies, and local-global path adjustments.

D. Mid-air collision avoidance using Inverse Proportional Navigation (IPN)

Rejoining the formation poses a collision risk with obstacles or other agents. Inverse Proportional Navigation (IPN) [28], [29] is used to reduce this risk. IPN is a straightforward and effective approach derived from Proportional Navigation (PN), commonly used in missile guidance. IPN requires the aircraft to adjust against the Line Of Sight (LOS) rate to avoid collisions.

V. Path planning strategy

A. The activation of the Dynamic Autorouting (DA) mode

1) Scenario 1: The Loss of Communication: The DA mode activates upon losing the communication network. This situation presents two cases: 1.1) the disconnection of the followers and 1.2) the disconnection of the leader. Agents with intact communication will continue in formation flight. If the leader's connection is lost, all followers will switch to DA mode, as they need the leader's information to maintain formation.

2) Scenario 2: Encountering Dynamic Obstacles: The DA mode will also activate when encountering dynamic obstacles. This includes 2.1) a follower encountering an obstacle and 2.2) a leader encountering an obstacle. In the first case, the agent will activate DA mode independently to avoid the obstacle. In the second case, it is unsafe to follow the leader, prompting all followers to activate DA mode until safety is restored.

B. Coordination strategy for multi-agent systems

The coordination framework between the leader and the followers is depicted in Fig. 4. When dynamic obstacles come within a threshold ϵ, `flagDanger=1` is activated. In scenarios where both of them are deemed safe (`follower.flagDanger=0` and `leader.flagDanger=0`) and the leader maintains an active status (`leader.flagComs=1`), the follower engages in leader-following formation utilising DNDI. Otherwise, the follower disengages from the formation and navigates independently using the DA program, unless a mid-air collision alert is triggered, prompting it to execute IPN as a final avoidance strategy. The pseudocode for the follower is detailed in Algorithm 2.

Algorithm 2 Path-planning strategy for followers

Initialization: Generate a global path using IFDS for the leader considering static obstacles.
Set: $n,\ A,\ X_{i0},\ V_{i0},\ \psi_{i0},\ \gamma_{i0},\ \xi_f,\ \epsilon$
while $||\xi - \xi_f|| < \epsilon$ **do**
  if `follower.flagDanger=0` **and** `leader.flagDanger=0` **and** `leader.flagComs=1` **then**
    Execute `Leader_follower_DNDI()`
  else if `follower.flagIPN=1` **then**
    Execute `IPN()`
  else
    Execute `DA()`
  end if
  Execute `follower.updateStates()`
end while

VI. Simulation Study

The flight simulation is conducted using MATLAB. The leader UAV flies at a cruising speed of $10\ m/s$, starting from the coordinate $(0,\ 0,\ 0)\ m$ and heading towards its destination at $(200,\ 0,\ 10)\ m$. Five follower agents are assigned to follow the leader in a Vic formation, as shown in Fig. 3, while maintaining the minimum inter-agent distance of $2\ m$. This group of UAVs is manoeuvring through a path that includes 1) eight stationary obstacles and 2) three stationary obstacles along with two moving obstacles. There will be a duration during which communication is disrupted among them. The simulation concludes when the group of UAVs approaches within a $1\ m$ range of the destination.

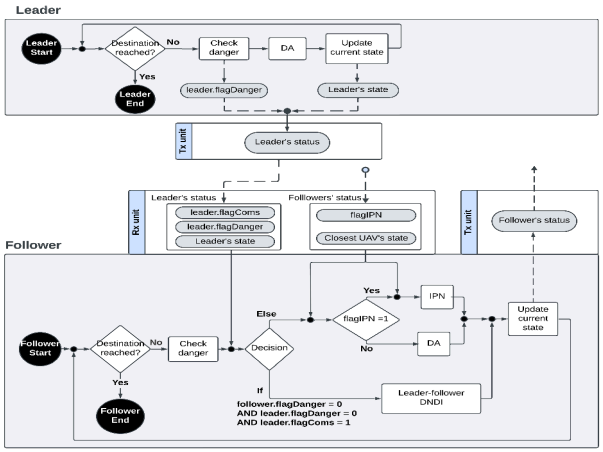

Figure 4: Multi-agent path-planning strategy.

VII. Results and Discussion

Fig. 7 illustrates the first scenario. The leader and all follower UAVs took off in a Vic formation within a fully connected communication network. After five seconds, we lost connection with Agent 4 and Agent 5. In this instance, Agent 4 and Agent 5 were navigating separate paths using the DA program, while the remaining agents continued to uphold the formation. At $t = 10\ s$, the leader went offline. This prompted all followers to abandon the formation, activate DA, and proceed individually towards the target area. By $t = 25\ s$, the connection was restored between the leader and all agents, except for Agent 5. Agents 1 - 4 returned to their designated formation positions, while Agent 5 continued towards the destination independently. Throughout the flight, each agent maintained a safe inter-agent distance exceeding $2\ m$, with the minimum observed distance being $7.8\ m$, as shown in the relative distance graph in Fig. 5.

In the second scenario, the dynamic obstacle was encountered at times $t = 6\ s$, $14\ s$, and $t = 18\ s$. All agents successfully switched to DA mode to avoid the obstacle before returning to formation flight. The formation error is illustrated in Fig. 6. The mean absolute formation errors for agents 1 to 5 were $3.08\ m$, $3.16\ m$, $5.75\ m$, $6.91\ m$, and $9.62\ m$, respectively. When obstacles were cleared, the DNDI algorithm kept the absolute formation error under about $3.5\ m$.

VIII. Conclusion

This research presents an innovative multi-UAV path planning technique. It consists of independent Dynamic Autorouting (DA) through the Interfered Fluid Dynamical System (IFDS) and consensus leader-following for formation flight via Distributed Nonlinear Dynamic Inversion (DNDI). Our approach is based on analytical frameworks, which guarantees efficiency and real-time performance. The strategy yielded successful results, with agents preserving their formation, avoiding collisions, and reaching target destinations despite unforeseen circumstances such as communication failures and

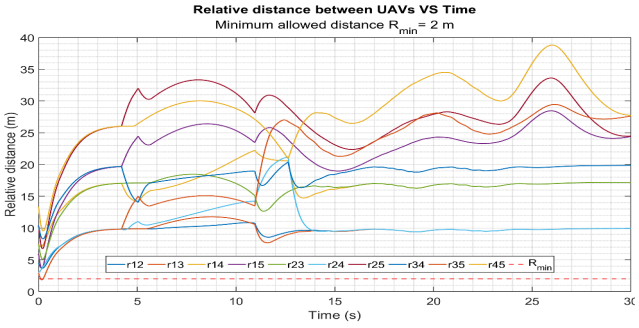

Figure 5: Relative distance between agents in scenario 1.

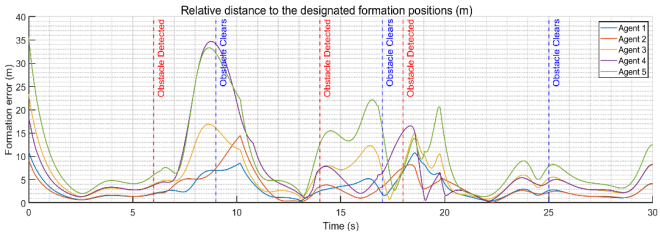

Figure 6: Formation errors in scenario 2.

dynamic obstacles. All UAVs consistently maintained a distance that exceeded 5 m. This strategy allows a group of UAVs to be effectively adapted to a rapidly changing environment. However, a major limitation is the need for manual hard-coding of decision-making logic to cover all scenarios. This indicates a need for more automated or adaptive decision-making frameworks. In addition, future research could investigate how different communication strategies affect coordination and efficiency in multi-agent systems.

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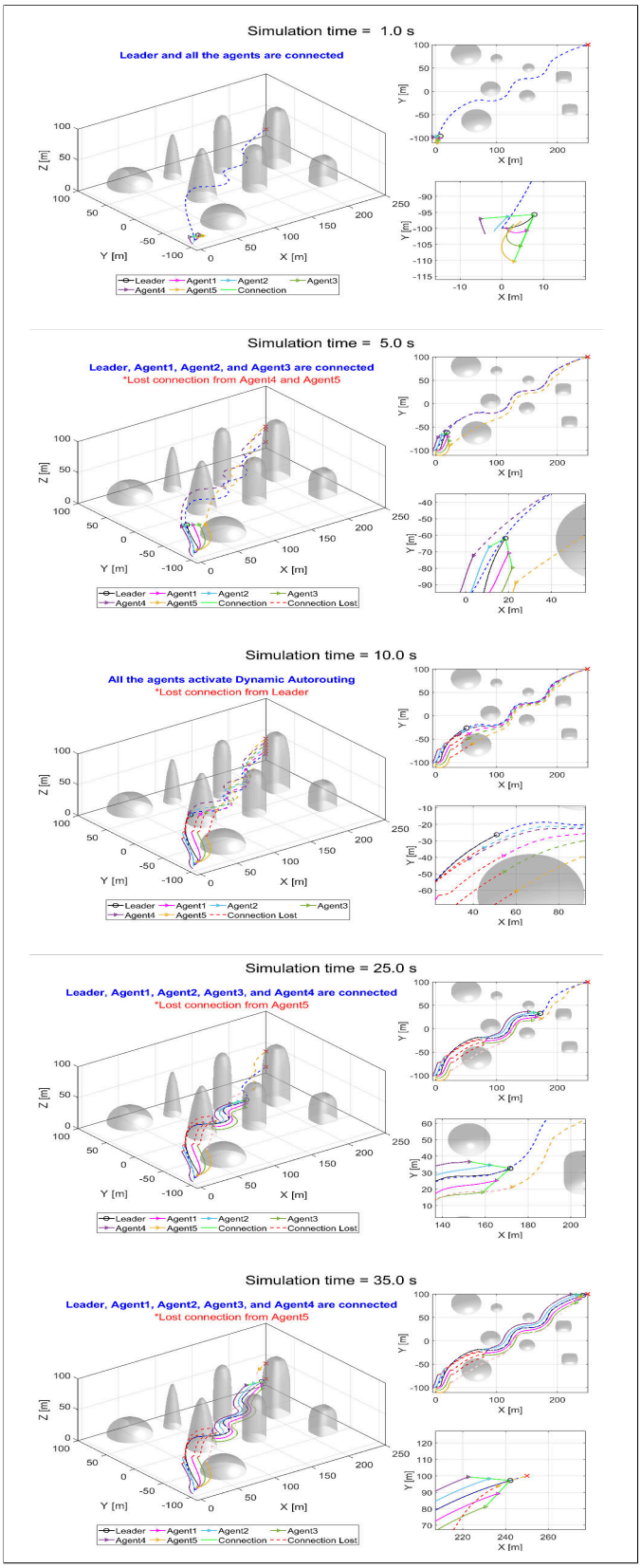

Figure 7: Scenario 1: Loss of communication, $t = 1 - 35$ s.

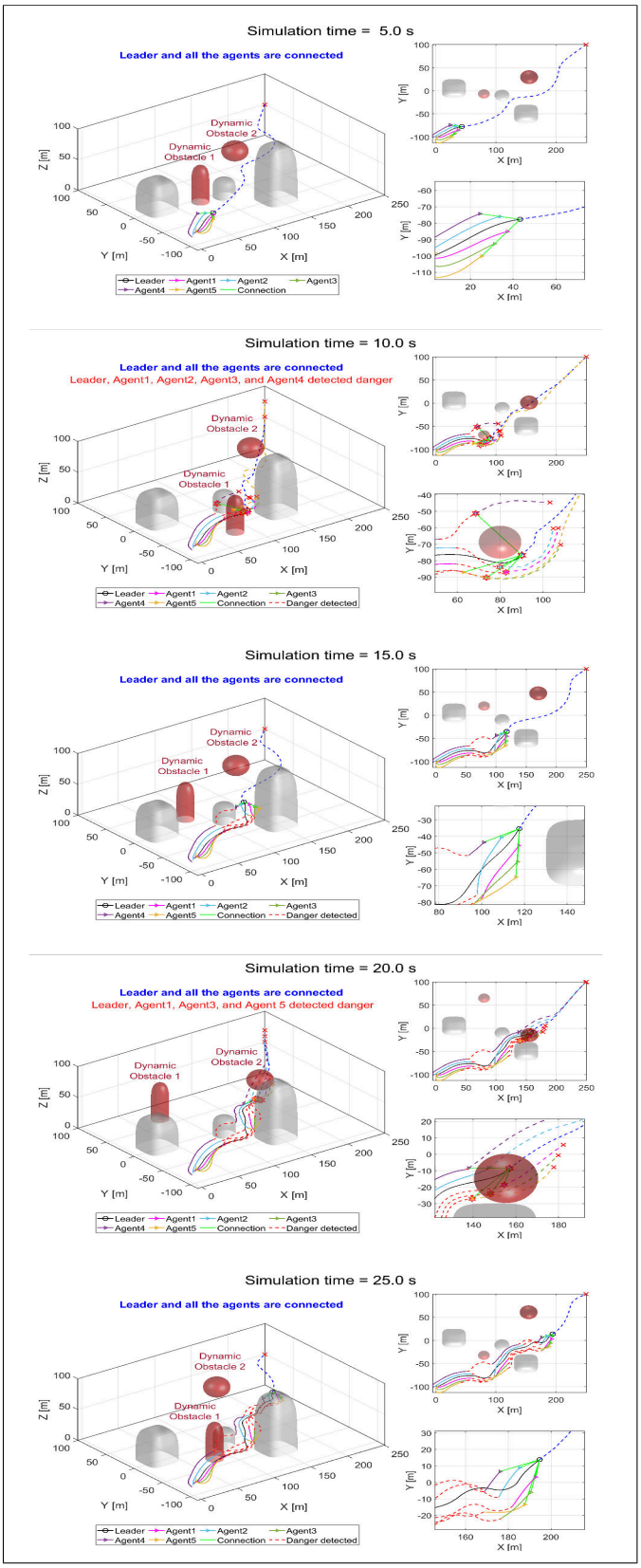

Figure 8: Scenario 2: Dynamic obstacles, $t = 5 - 25$ s.

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Tamanakijprasart, Komsun; Mondal, Sabyasachi; Tsourdos, Antonios

2025-07-01
Institute of Electrical and Electronics Engineers (IEEE)
https://doi.org/10.1109/iccad64771.2025.11099262
Tamanakijprasart K, Mondal S, Tsourdos A. (2025) Multi-agent path planning in dynamic environment with communication disruptions. In: 2025 International Conference on Control, Automation and Diagnosis (ICCAD), 1-3 July 2025, Barcelona, Spain

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